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# Fuzzy model for estimating induction dose for general anesthesia

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At present, anesthetist estimates initial anesthetic dose required to produce induction in general anesthesia. This paper proposes a fuzzy model for deciding this dose based on patient data (age, gender, height and weight) and computes the dose by defining IF-THEN rules between age and body surface area. Deviation of predicted initial anesthetic dose from the actual dose given by the anesthetist to patients (9) was found to be within ± 7%.

**Keywords**: Body surface area, Fuzzy logic, Initial anesthetic dose, Induction

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## Introduction

Main activities of anesthetists in the operation room comprise of administration of anesthetic dose to the patient, determination of depth of anesthesia and producing muscle relaxation. Administration of anesthetic dose is a two-step process–initially giving induction dose and later maintaining anesthesia during surgery. Anesthetist administers the dose based on age, gender and weight of the patient and analyzes excessive amount of information in a short span[1]. Such a situation places great demands on the vigilance and objectivity of the anesthetist[2]. This analysis becomes most difficult at precisely the time when it is most critical[3] and anesthetist makes heuristic decisions on the dosage. Overdosing and underdosing during surgery are common with general anaesthesia[4,5] which impede smooth transition of patient from awake to anesthetized state.

Studies are available on anesthesia management and not on dosage calculations. ATTENDING system[6] examines an anesthetist's proposed plan for an operation. This program has mainly been used for training[7]. A knowledge-base system[8,9] offers decision support during cardiovascular surgery. A few other fuzzy based systems attempt to monitor anesthetic depth[10,11]. This study presents an expert system combining knowledge representation, fuzzy information and inference structure.

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## Materials and Methods

### Experiment

Hospital Ethics Committee of PGI Chandigarh approved the protocol and written consent was taken from each patient. Nine patients, free from any neurological disorder or other disease were premedicated with 5-10 mg diazepam about 2 h before the start of surgery. Induction of anesthesia was done with thiopentone and each patient was given the dose by anesthetist according to his experience. Vecuronium (0.1 mg/kg) was administered to produce muscular relaxation. After endotracheal intubation, patient was prepared for maintenance of anesthesia and surgery.

### Fuzzy Knowledge Model for Induction Dose

Amount of anesthetic dose, which bears a direct relation to age, body surface area and gender of the patient, is very difficult to model mathematically and therefore, one has to go for fuzzy modeling. To build fuzzy model of this relationship, input variables were taken as age and body surface area (BSA) of the patient. BSA is defined as[12]:

$$\text{BSA} = 0.007184^{*} (\text{weight})^{0.425} {}^{*} (\text{height})^{0.725}$$

Here weight is in kg and height in cm.

Output of the model is initial dose. The input values corresponding to different patients are not fed directly to the fuzzy logic controller. The data is checked first for validity and then scaled down to the [0 1] range. The normalization was done with respect to the limiting values.

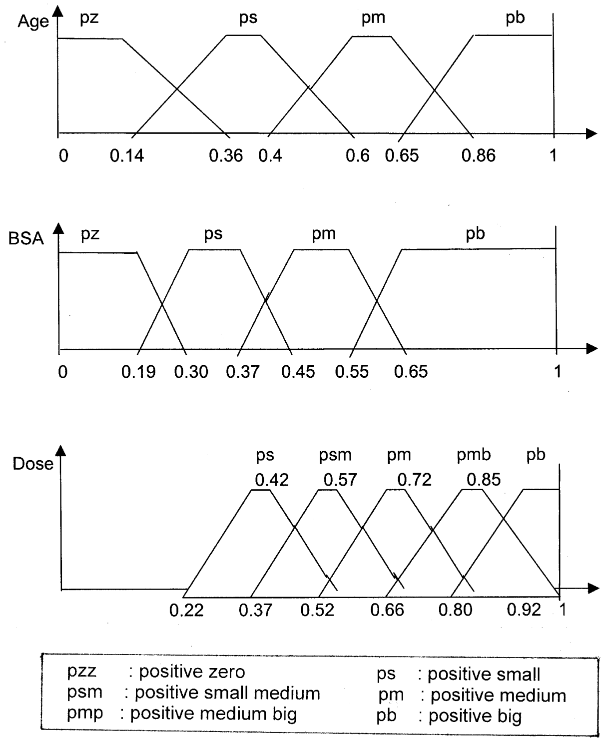


Fig. 1—Membership functions of input (age and BSA) and output (induction dose) parameters

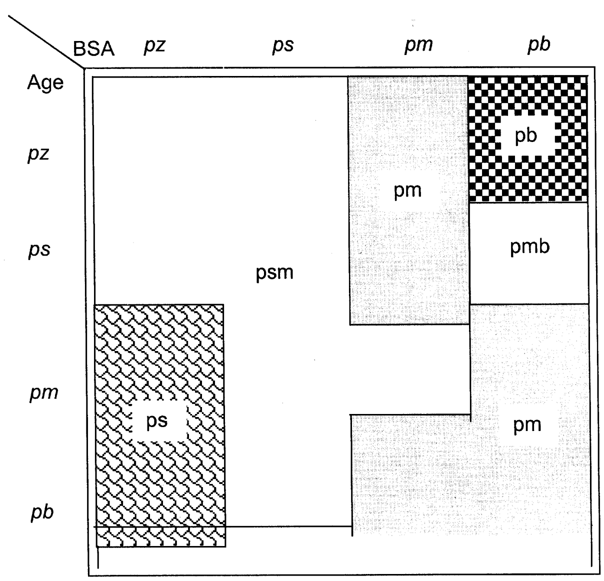


Fig. 2—Term sets and IF-THEN rules of fuzzy system for initial dose determination

There are no specific rules as to the number of membership functions corresponding to a given input variable. It is a tradeoff between the structural complexity of the rule base and the accuracy of the output. Various membership functions of the two inputs and one output were tried and the configuration

Table 1—Demographic data of patients

| ID No. | Gender | Age, Y | Height, cm | Weight, kg |
|---|---|---|---|---|
| 1 | M | 41 | 174 | 74 |
| 2 | F | 30 | 147 | 72 |
| 3 | F | 45 | 162 | 56 |
| 4 | F | 23 | 160 | 60 |
| 5 | F | 52 | 150 | 58 |
| 6 | F | 41 | 154 | 67 |
| 7 | F | 21 | 152 | 68 |
| 8 | F | 56 | 157 | 56 |
| 9 | F | 29 | 148 | 51 |

Table 2—Limiting values of input and output variables

| Variable | Range | Normalization values | |
|---|---|---|---|
| | | Minimum | Maximum |
| Age, Y | 21-56 | 20 | 80 |
| BSA, height in cm, weight in kg | 1.39-1.88 | 1.2 | 2.2 |
| Initial dose, mg | 220-370 | 110 | 500 |

resulting in maximum accuracy of output values was selected. Accordingly, fuzzy sets (Fig. 1) were defined on each of the input space (4) and on the output space (5).

Since four membership functions are associated with each input, the input space is partitioned in $4^2$ = 16 fuzzy subspaces, each of which is governed by a fuzzy IF-THEN rule. 'Mamdani' fuzzy inference system is used for defining membership functions and rule base (Fig. 2). Every rule consists of two parts – *Premise* part of the rule operates in fuzzy subspace of inputs while *Consequent* part describes the output within the fuzzy subspace of output. Defuzzification was done using 'Centroid Rule'. Gender correction was applied for female patients at the end taking it as 90% of the value in males. The same thumb rule is applied by the anesthetists in the operation theatre.

## Results and Discussion

The demographic data of patients is given in Table 1. An initial dose computation system depending upon age, height and weight of the patients was realized using the fuzzy IF-THEN rules with gender correction. The patient's height and weight were measured outside the operation theatre and dose was determined before the patient was handed over to the anesthetist, who was kept unaware of the value of computed dose and was allowed to inject thiopentone intravenously in his routine manner. Amount of the drug was noted down in all patients. Table 2 shows extreme values of variables and the values used for normalization, whereas Table 3 shows the crisp values of initial drug dosage predicted by the system

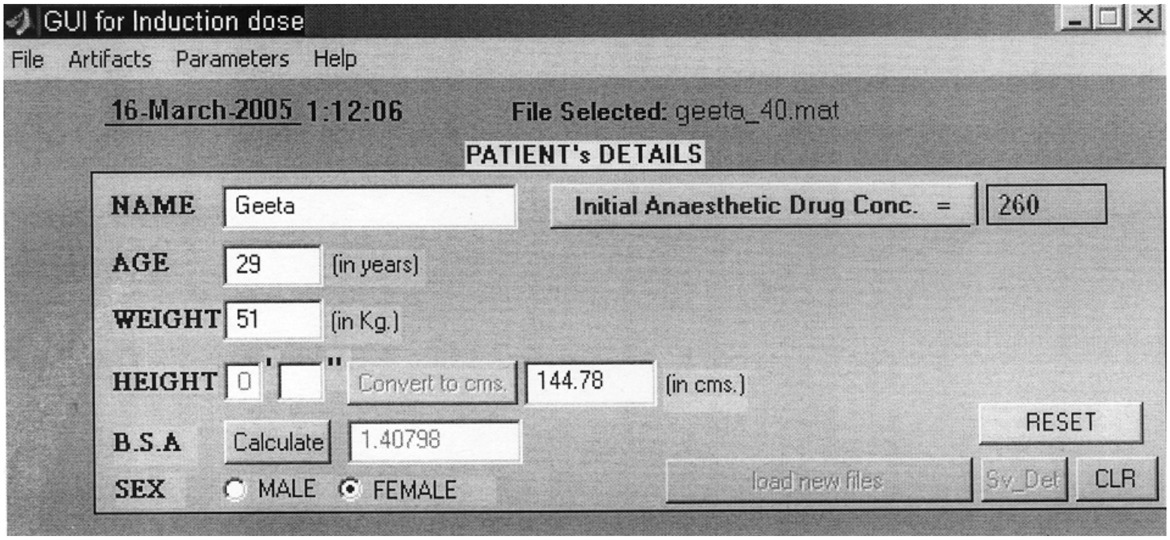


Fig 3—Graphic user interface for computing induction dose. User enters the patient details and computer program displays the calculated dose value

Table 3—Dosage predicted by fuzzy system and actually administered dose

| ID No. | Calculated dose, mg | Actual dose, mg | Error % |
|---|---|---|---|
| 1 | 359 | 370 | -3.0 |
| 2 | 343 | 360 | -4.7 |
| 3 | 236 | 250 | -5.6 |
| 4 | 324 | 310 | 4.5 |
| 5 | 210 | 220 | -4.5 |
| 6 | 274 | 290 | -5.5 |
| 7 | 355 | 340 | 4.4 |
| 8 | 218 | 230 | -5.2 |
| 9 | 257 | 240 | 7.0 |

vis-à-vis the actual dose given to them. A graphic user interface, which prompts the user data to be entered and displays the amount of dose to be given to patient, was also developed (Fig. 3).

The values of initial dose of thiopentone as predicted by the system were checked against the actual values of dose delivered to the patients in the operation theatre. There was a maximum deviation of ±7% in the two values. The output of the proposed fuzzy knowledge model offers all the desirable features of a drug dosage estimator. The model has the following advantages:

**Gradation**

Output dosage is not discrete, rather it scales the graded values. In present case, range was 200-400 mg. The dose is automatically calculated as soon as height, weight, age and gender information is fed into the program.

**Accuracy**

By comparing the predicted dose with actual dose given by the doctor, it may be stated that calculated dose is quite accurate.

**Convenient**

Dose may be calculated in real-time before the patient enters operation theatre. If the system is implemented in hospitals, anesthetist will be free to attend to other functions related to the patient.

The algorithm for dose calculation takes into account all the required factors. The parameters height, weight, age and gender remain at the back of anesthetist's mind and he unknowingly makes some calculations with these parameters when he administers the induction dose to patients. However, there is no simple mathematical relationship, which can be derived among the variables, as the mapping from input to output is highly nonlinear. Combined use of these parameters with fuzzy technique as a mapping tool results in the desired performance.

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